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Optimally Learnt, Neural Network Based Autonomous Mobile Robot Navigation System

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Abstract— **Neural network based systems have been used in past years for robot navigation applications because of their ability to learn human expertise and to utilize this knowledge to develop autonomous navigation strategies. In this paper, neural based systems are developed for mobile robot reactive navigation. The proposed systems transform sensors' input to yield wheel velocities. Novel algorithm is proposed for optimal training of neural network. With a view to ascertain the efficacy of proposed system; developed neural system's performance is compared to other neural and fuzzy based approaches. Simulation results show effectiveness of proposed system in all kind of obstacle environments.**

Index Terms— **Mobile robot; Reactive navigation; Neural Network, Optimal learning, Supervised learning**

I. Introduction

Autonomous robot navigation [1] means the ability of a robot to move purposefully and without human intervention in environments that have not been specifically engineered for it. Autonomous navigation requires a number of heterogeneous capabilities like ability to reach a given location; to reach in real time to unexpected events, to determine the robot's position; and to adapt to changes in the environment. The general theory for mobile robotics navigation is based on a following idea: the robot must *Sense* the known world, be able to *Plan* its operations and then *Act* based on the model. When a robotic system is described as *fully autonomous*, then it is designed to be operated always without external human control. This is to be distinguished from *Semiautonomous* robots in which a human operator is required full time but where the robot is permitted to make certain decisions on its own.

Various approaches are found in literature for mobile robot navigation including neural and fuzzy based systems. Despite the impressive advances in the field of autonomous robotics in recent years, numbers of problems remain. Most of the difficulties originate because of real-world and unstructured environments resulting into uncertainties. These uncertainties are in terms of prior knowledge about the environment, perceptually acquired information, limited range, adverse observation conditions (e.g. poor lighting), complex and unpredictable dynamics. Other problems are related to the requirement that the behavior of the robot must be reactive to dynamic aspects of the unknown environments and must be able to generate robust behavior in the face of uncertain sensors, unpredictable environments and changing world.

Many approaches are applied to solve above mentioned challenges in robot navigation problem. Some of the approaches focus on path planning methods [2]. Another approaches use potential field [3] in which the robot-motion reaction is determined by the resultant virtual force. Several other approaches have used statistical methods, Partially Observable Markov Decision Process (POMDP) or reinforcement learning schemes. Some approaches use the application of artificial neural-networks (ANN) [4,5] for reactive control. The advantage of this approach is the learning capacity of the neural network, however, many times learning convergence is very slow and generalization is not always satisfactory. Several other methods exploiting neural-fuzzy network schemes ([6]-[14]), have been proposed for avoiding unexpected obstacles. Humans have a remarkable capability to learn and perform a wide variety of physical and mental task and generalization of that knowledge. Neural network tries to mimic human expertise with formal methodology for representing and implementing the human expert's heuristic knowledge and perception based actions. Our proposed system's conceptualization is analogous to that indicated in general terms by [6]; while our actual detailed system is new. The rest of this paper is organized as follows: In Section II, we introduce proposed algorithm for the development of the neural based reactive navigation algorithm. Simulation results are presented in Section III. We conclude the paper in Section IV.

II. Proposed algorithm for Navigation

We propose, an algorithm for mobile robot's reactive navigation in presence of obstacles using neural based system. Proposed algorithm overcomes the shortcoming of current approaches in terms of learning mechanism used. The problem formulation for basic motion planning problem, in general terms is as follows[8]: Let *A* be the single rigid object –the robot – moving in a euclidian space *W*, called workspace, represented as R^N, with N= 2 or 3. Let $B_1, B_2 \ldots Bq$

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be the fixed rigid objects distributed in *W*. The B_i's are called obstacles. Assume that both geometry of *A*, B_1, B_2...B_q and the locations of B_i's in W are accurately known. With assumptions that no kinematics constraints limit the motion of *A*, *g*iven an initial position and orientation; a goal position and orientation of *A* in *W*, generate a path *T* specifying a sequence of positions and orientations of *A* avoiding contact with B_i's, starting at the initial position and orientation; and terminating at the goal position and orientation.

A. Mobile Robot Configuration

We consider two dimensional workspace for mobile robot as shown in Fig.1. Mobile robot is having initial coordinates as x-coordinate (x_o) and y-coordinate (y_o). Similarly, target position coordinates are denoted as x_t and y_t respectively. Mobile robot's current position (calculated and updated at each step) can be denoted as x_{curr} and y_{curr}, angle between target with respect to positive y axis is è$_{tr}$. Robot's pose (head) with respect to positive y axis is considered as è$_{hr}$, è$_{head}$ is the heading angle between target and robot current position, *Span* (S) is the distance between left and right wheel, V_l and V_r are mobile robots left wheel and right wheel velocities, respectively.

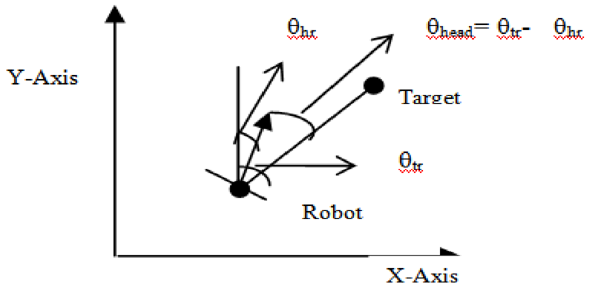

Figure 1. Mobile Robot Configuration

The mobile robot has two independently driven co-axial wheels. We consider a mobile robot with differential drive wheel. Initial and final positions are known to the robot at all the time. At each step, current location and orientation are computed. No history of past sensor readings are retained and thus robot is having pure reactive navigation. Obstacles may be stationary or may be mobile.

B. Sensors Arrangement, Quantization of Sensor Values & Defining Heading angles

In our algorithm, we consider robot fitted with N equally spaced ultrasonic sensors in the front. If the front (head) of the robot is at 0 degrees (w.r.t. +y axis), then the sensors are located between -90 to +90 degrees each being separated by è$_s$ degrees as shown in Fig. 2.

Considering d(i)–ultrasonic data for i[th] sensor; distances to the obstacles may defined as below:

Left_obs = min{d (i)} where, i= 1,2…x.
Front_obs = min{d (i)} where, i= x+1,x+2 …y.
Right_obs = min{d (i)} where, i= y+1, y+2,.. N

Where, x, y are integer numbers.

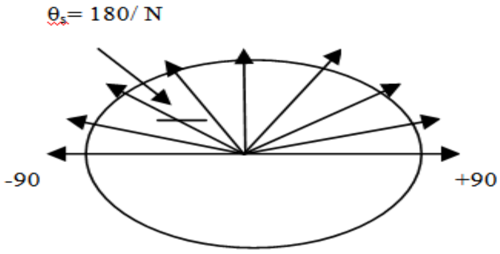

Figure 2. Arrangement of ultrasonic sensors

Grouping and Quantization of the Sensor values:

These sensor values are grouped and quantized before sending into the intelligent network. Sensors grouping will enable mobile robot for better environmental sensing by optimizing computational complexities to the speed of computation. Quantization formula for groups (X_i) where, i=1, 2...M (M<=N) is as follows:

$$X_i = \begin{cases} 1 & \text{for } 0 < d_i <= D_1, \\ 2 & \text{for } D_1 < d_i <= D_2, \\ 3 & \text{for } D_2 < d_i <= D_3, \\ . & . \\ M & d_i\ i > D_M. \end{cases}$$

Where, d_i is the minimum sensor value of the i[th] group and $D_1, D_2 \ldots D_M$ are threshold values for quantization.

Defining Heading Angle :

We define heading angle (è$_{head}$) as follows:

We define heading angle (θ_{head}) as follows:

If $\theta_{head} < p$ then $\theta_{head} = \alpha$,
If $p <= \theta_{head} <= q$ then $\theta_{head} = \beta$,
If $q <= \theta_{head}$ then $\theta_{head} = \gamma$.

Once surrounding environmental sense process is competed; set of information is available for planning. Next step is to train intelligent system with these set of information. As stated earlier, neural systems have capabilities to learn, generalise and then perform intelligent task based on learning. Next subsections describe training neural based system.

C. Neural Based System

Neural networks have got remarkable generalisation capabilities, once trained properly. We consider single stage neural based architecture as shown in Fig.3. Our System's conceptualization is based on [6] however; overall design is entirely new based on optimal learning algorithm defined in next sub-section. Our proposed framework contains optimum learning of neural networks that overcomes the problems faced by existing approaches. Neural network has M inputs derived from grouping of sensors. Out of them, M-1 inputs are the distance information from the various obstacles present in robot's perceptual environment. The last input is the heading angle. Neural network processes this information and drives the output wheels of mobile robot.

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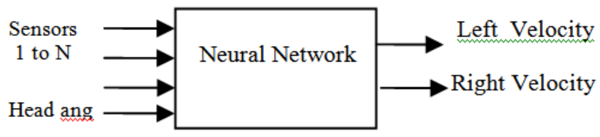

Figure.3 Proposed neural based system

Input sensory information's cardinality can be kept higher for neural network to take maximum advantage of neural networks learning capabilities.

D. *Proposed Training algorithm for neural network*

Training of intelligent system is crucial for successful navigation of mobile vehicle. Training is difficult in the sense that input space may contain infinitely many possibilities and mobile robot needs to learn them effectively. Many times mobile robot also needs to execute operations in hazardous environments like fire or space missions where, online training is not feasible. Off line training is possible in such cases. Mobile robot has to sense environment in real time and also to make precise decision, based on learning. Few training approaches are found in literature i.e. a) generating training sequences by experimental set up and b) heuristic approach based on expert rules. In the first approach (training by experimental setups), learning is done by setting different environmental set ups. i.e. different start, end (target) positions, different obstacles positions etc. In this case, number of training pairs resulted for different input pairs may not be evenly distributed. Some of the input pairs may appear more number of times, while some may appear lesser or even not appear. Training may not be considered optimum as; for some inputs patterns are not learnt while some are over learnt. In case of second alternative (training by expert rules [7]), training is done by fewer number of input patterns. This type of training may save training time, may give good performance in some cases but, they may not perform well in all kind of environmental conditions. This is because of the fact that selection of training pairs is for particular task and they do not represent entire space uniformly. Hence, their output in unexplored space of input space is not guaranteed.

We propose, mobile robot's training based on uniform sampling that overcomes the problems with above mentioned methods. The proposed algorithms not only takes samples from entire sample space (to provide heterogeneity), also takes equal number of sample data from all possible input space (to provide homogeneity). In the proposed algorithm, actual sensor readings are considered to be quantized in to k linguistic values. Uniform sampling of these quantized values will enable us a) to consider entire space of input region and; b) will enable us to generate optimum number of training pairs required for training.

In the proposed approach, we train the network as follows:

1. First, let input cardinality (number of sensor inputs) of the neural networks equal to M. Also, assume that each input takes k linguistic values (e.g. near, medium, far). Then we can generate total k^M training pairs.
2. Second, output values of each of these input patterns are decided based on experimentation or by expert rules.
3. Neural network is trained accordingly to the training pairs generated and performance of the network can be checked using proper evaluating function e.g. MSE (mean square error)
4. If any correction is required; make adjustment to step no. 2 and then repeat steps.

E. Heuristic Neuro System Imitating Fuzzy Associated Rules (Based on song and sheen's work [7])

Inputs are range information acquired by an array of five ultrasonic sensors (input no.1 to 5) and a heading angle between the robot and a specified target called Head_ang (input no.6) as shown in Fig.4. The outputs from the neural network are left and right velocities of the two rear wheels of the robot denoted by Left_V and Right_V respectively. Training set values for this neural system is based on [7].

III.SIMULATION RESULTS

To demonstrate the effectiveness, robustness and comparison of various systems discussed in earlier sections, we present simulation results as follows. We have considered mobile robot having differential drive mechanism with wheels 50 cm apart diametrically (i.e. span of mobile robot).

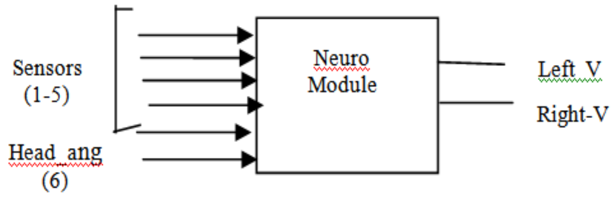

Figure 4. Heuristic neural system imitating Fuzzy associated rules

As first case, heuristic neural system imitating fuzzy associated rules (based on [7]) is simulated considering two layer feed forward back propagation network. Training pairs are generated based on training table used [7]. Training was done with different numbers of neurons in hidden layer. In each experiment 10000 training steps were used. Training was started with 4 neurons in hidden layer and then gradually increased the numbers of neurons to 6,8,10. In first three cases error performance was poor. In the case of 10 neurons Mean Square Error (MSE) reduced to 0.17.

As the second case, our proposed system is simulated with total ultrasonic sensors (N) equal to 9.These Sensors are equally separated by $è_s$ =ð/8 and detect the distance of obstacle along the radial direction up to *300 cm.* The wheels can have a maximum velocity up to *30 cm/s*. Sensor input dimensions to the neural system are kept to three (i.e. M=3). Threshold values considered are D_1=100 cm and D_2=200cm. In order to define heading angle ($è_{head}$), we have taken p, q, á, â, ã values as -ð/8, +ð/8, 1, 2, and 3 respectively. Left, front and right obstacles are considered equally important and hence to find the effective inputs to the neural systems. As the final value for each group, we

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take the minimum value among the corresponding sensors readings which are fed to neural system module. Final network's weights and thresholds are selected by simulating the neural module in many different environments and measuring mean square errors.

Two layers feed forward back propagation network (FF-BPN) is used for mapping the input quantized values to the output wheel velocities. Batch mode of training is used. As shown earlier, for optimum learning we have used total 81 training pairs. After training the mean square error was reduced to 0.03 after 10,000 iterations. There are total 4*3 + 3*2 + 3 + 2= 23 adjustable parameters including weights and biases. Training pairs to parameters to be adjusted ratio is kept nearer to 3.5. Error function is used as –mean square. The neural network structure emerged as the training results is shown as Fig. 5 and final weights for adjustable parameters after training are is shown as Fig. 6.

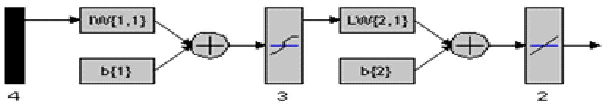

Figure 5. Neural network training structure

Input layer –hidden layer weights

0.9064 0.2270 0.6740 -2.1219
0.9263 0.9251 -0.0998 -0.1912
0.9313 0.9305 -0.0967 -0.1911

Final Input layer –hidden layer weights:

-0.1468 -40.3582 40.2622
0.1172 34.9644 -34.7848

Bias terms to the hidden layer

1.5691 ; -2.8799 ; -2.9094

Bias term to the output layer

0.4431 ; 0.4050

Figure 6. Final weights of adjustable parameters after training

As third case, we have simulated fuzzy based system, as fuzzy based systems are also widely used for mobile robot navigation. Fuzzy logic provides formal methodology to perceive human expertise into machines. The details of fuzzy based approach, structure, fuzzy behaviors, behavior fusion, simulations and other details can be found in our earlier work [13].

Robot Navigation with neural based system

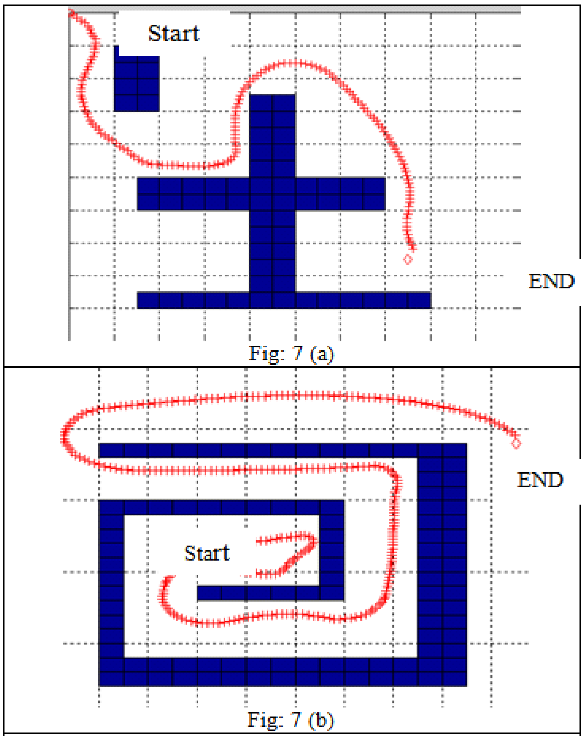

Fig:7(a-b) Robot navigation with neural based system

Fig.7(a-b) shows robot navigation with neural based system in different environmental conditions. We have shown the robot navigation for avoidance of obstacles with different behaviours like target steer, obstacle avoidance and wall following in various environments i.e. U- shaped, narrow vertical road, narrow horizontal road, other shapes and also in the clutter environment. Fig. 7(a) shows robot navigation for complex obstacle. From the start position it tries to execute target steer behaviour to the END position. When mobile robot finds obstacle in the path, it tries to perform obstacle avoidance behaviour and then continuing with wall following behaviour it comes out of obstacle and then steers towards the target.

Comparison of Robot Navigation with neural system to heuristic neural and Fuzzy based systems Fig.8 illustrates comparison of robot navigation with neural system to heuristic neural system and also to fuzzy based system. It is clear that paths are different in the case for SS based NN approach (song and sheen based heuristic neural network) to our developed neural and fuzzy based system. This is because decision rules used are different for training algorithms. However, we can clearly make comparison based on smoothness of the path traversed and it is cleared than our proposed both systems outperforms heuristic based neural approach [7]. The result highlights the fact that heuristic based approaches do not give good performance in all conditions while; optimally learnt networks perform well in general. Simulation results also highlight the fact that proposed neural based system gives comparable results to our earlier developed fuzzy system [13]. Neural network gives slightly inferior performance compared to fuzzy based

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system while; processing information of unexplored region while training. However, this does not rule out importance of neural system in robot navigation application. Neural networks do point to point mapping compare to set to set mapping given by fuzzy systems and hence, are more efficient in terms of computational complexities than fuzzy based systems. The same fact is observed for multiple simulations done with various environmental conditions. Fig. 8 Comparison of Robot navigation of neural (NN) approach to heuristic neural (SS based) and Fuzzy (FIS) based systems

IV.CONCLUSIONS

In this paper, a new approach for neural based robot navigation is discussed. The mobile robot performs reactive navigation and suitable for real time, dynamic environment rather than looking for optimal path as performed by path planning techniques. Simulation results for mobile robot navigation with neural based system demonstrate the good performance in complex and unknown environments navigated by the mobile robot. Simulation results suggest that proposed optimally learnt neural network performs better than earlier developed heuristic neural approaches. Simulation results also suggest that, for control side neural network does not give better performance in comparison to fuzzy system. However, information on environment (Sense) may be obtained by neural networks as, complex environmental conditions having higher dimensionality; fuzzy systems will not give optimal results to capture inputs to the intelligent networks. Currently, our work is in progress for neuro-fuzzy based hybrid approach. Also algorithms may be developed for multiple robots cases and comparison can be with other neuro fuzzy based approaches.

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